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Wavelet Based Processing of Physiological Signals for Purposes of Embedded Computing

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Abstract—The Wavelet Transform in its discrete form has been applied to a wide range of biomedical signals by now. Typically, its calculation is performed off-line and calculation systems suffer from limited autonomy, bulkiness and obtrusiveness. A surge in industrial, research and academic interest into telemedicine and medical embedded systems, has been noticed recently, where miniature, low-cost, autonomous and ultra-low-power devices play a major role. Such devices are usually based on microcontrollers, which in addition to other tasks need to perform signal processing, very often in real-time. This paper presents a methodology to perform wavelet transform on general purpose microcontrollers. By using its optimized versions the electrocardiogram and photoplethysmographic signals are processed in real time for the purposes of QRS complex extraction and denoising. After the theoretical considerations on wavelets and their optimization in integer arithmetic, the embedded hardware and software computation architectures are described. The following is the presentation of obtained results during intensive tests on real signals. The same approach can be applied with other signals where the embedded implementation of wavelets can be beneficial.

Keywords—wavelet transform; microcontroller; QRS; denoising

I. INTRODUCTION

The Fourier Transform (FT) contains only globally averaged information and so has the potential to obscure transient or location specific features within the signal. This limitation can be partly overcome by Short Time Fourier transform (STFT) which uses a sliding time window of fixed length to localize the analysis in time. Among a number of alternative time–frequency methods, which are today available the most promising seems to be Wavelet Transform (WT).

In contrast to FT which is restricted to the use of a sinusoid the WT uses a variety of basic functions, known as wavelets [1]. In its discrete form (DWT), based on orthogonal wavelet, it is particularly useful in signal compression. Another advantage of WT is the possibility to denoise signal, using successive procedures of decomposition, thresholding, and signal reconstruction.

DWT analysis has now been applied to a wide range of biomedical signals including ECG, EMG, EEG, PPG, clinical

sounds, respiratory patterns, blood pressure trends and DNA sequences [2]. Very often, it is calculated off-line by custom-design software or widely used mathematical tools like MATLAB. The input data are prerecorded in special data buses and formats, like MIT-BIH, or taken from logger devices, like holters or memory cards. These facts limit the flexibility and transferability of computation systems.

Today, the telemedicine and medical embedding systems are among the fastest growing areas, based on miniature, low-cost, autonomous and ultra-low-power devices, where microprocessors/microcontrollers (MC) perform major tasks. In addition to digitalization, data storage and communication MCs need to perform real-time signal processing in all three domains: time, frequency and time-frequency. It is not a trivial task considering the algorithmic complexities and limited performances of MCs in terms of arithmetic power, memory resources, consumption budget etc.

Thus, there is an essential need to optimize variety of calculation algorithms, including those DWT based, for their implementation on MC platforms.

In this paper we show a way to optimize DWT transform for its calculation by general purpose, low-cost and low-power MCs. Although the principle can be implanted by any MC, as a target platform the MSP430 from Texas Instruments (TI) is selected. After theoretical background on wavelets and their integer arithmetic optimizations, the MC-based computation architectures for real-time QRS complex extraction and denoising are elaborated. The following is the presentation of the obtained results. The approach is verified on physiological signals like electrocardiogram (ECG) and photoplethysmograph (PPG), but it can be applied with any signal where embedded implementation of WT is required.

II. METHODOLOGY

A. DWT

In practice, DWT is computed by passing signal $X(n)$ through a Low-Pass (L_d) and a High-Pass (H_d) filters successively according to the Mallat's decomposition scheme shown in Fig. 1 [3]. For each decomposition level i , the L_d and

H_d filters are followed by downsampling operator $\downarrow 2$, what is in fact the reduction of sampling rate by 2. The coefficients $CA_i(n)$ (approximations) and $CD_i(n)$ (details) are outputs from level i . The reconstruction consists of upsampling by $\uparrow 2$ and filtering by filters L_r and H_r . The coefficients for L_d , H_d , L_r , H_r filters can vary from the simplest, such as Haar, over Daubechies up to those such as Quadratic Spline. They have different vector lengths and, usually, floating point nature.

The Haar wavelet is considered to be the simplest one where $L_d=[1/\sqrt{2}, 1/\sqrt{2}]$, $H_d=[1/\sqrt{2}, -1/\sqrt{2}]$, $L_r=[\sqrt{2}/2, \sqrt{2}/2]$ and $H_r=[-\sqrt{2}/2, \sqrt{2}/2]$ filters are of two elements wide with real coefficients. Although very simple in principle Haar Transform (HT) is still complicated for implementation on MCs.

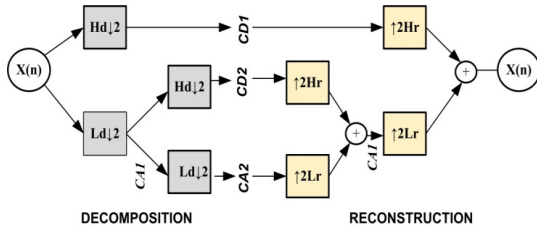


Figure 1. Wavelet decomposition and reconstruction scheme.

However, like any other WT, the HT can be generalized to an integer to integer version. One technique is proposed in [4] in form of S Transform (ST), which Forward (FST) and Reverse (RST) versions are defined as:

$$CA_I[n] = \left\lfloor \frac{1}{2} X[2n] + \frac{1}{2} X[2n+1] \right\rfloor, \quad (1)$$

$$CD_I[n] = X[2n] - X[2n+1], \quad (2)$$

$$X[2n] = CA_I[n] + \left\lfloor \frac{CD_I[n] + 1}{2} \right\rfloor, \quad (3)$$

$$X[2n+1] = CA_I[n] - \left\lfloor \frac{CD_I[n]}{2} \right\rfloor, \quad (4)$$

where $\lfloor \cdot \rfloor$ denotes rounding operator. The above equations employ only basic arithmetic units like adder/subtractor and shifter, because $\lfloor x/2 \rfloor = (x \gg 1)$.

B. WT in QRS Detection

As each WT, the FST is capable of distinguishing the QRS-complex within ECG signal by using Mallat's decomposition scheme. The $CD_i(n)$ coefficients across the scales show that the peak of the QRS complex corresponds to the zero crossing (ZC) between two modulus maxima within $CD_i(n)$ [2], [5]. Fig. 2 illustrates the decomposition of real discrete ECG signal $X(n)$ up to the 4th level, ($CD_1(n)$, $CD_2(n)$, $CD_3(n)$ and $CD_4(n)$) by using FST. For each decomposition level, the QRS complex produces two modulus maxima (min and max) with opposite signs, with a ZC between.

Presented method for QRS detection is very robust and allows direct application over the raw ECG data because the

frequency domain filtering is performed implicitly by computing the coefficients. For example, the original signal becomes clear at 4th decomposition level, as is shown in Fig. 2. The built-in filtering is an important feature of wavelet decomposition applied in QRS detection.

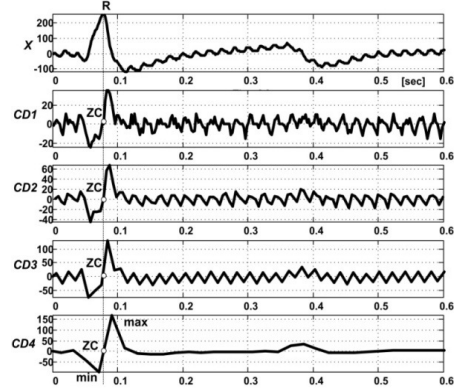


Figure 2. QRS detection using wavelet decomposition. Signal $X[n]$ is sampled with 800 Hz. $CD_i(n)$ are the details after i^{th} decomposition level.

In practice the selection of the most suitable decomposition level/levels is a challenge. Most of the energy for QRS complex lies between 3Hz and 40Hz. Translated to WT it means somewhere between scales 2^3 and 2^4 , with the largest at 2^4 . The energy of motion artifacts and baseline wander (i.e., noise) increases for scales greater than 2^5 .

Another complication is the acquisition of certain thresholds for finding the modulus maxima, because the values of thresholds differ, usually, from one level to another.

All mentioned restrictions and complications confine the method to off-line use and put heavy demand on the computing resources.

C. WT Based Denoising

WT should be effectively used in signal denoising, especially in elimination of high frequency and white noise [6]. The technique consists of the three successive procedures: decomposition, thresholding of the DWT coefficients, and signal reconstruction, Fig. 3. Firstly, the wavelet transform is derived to a chosen level N . Secondly, the thresholding of the detail coefficients from level 1 to N is performed. Lastly, the original signal is synthesized using the altered detail coefficients from level 1 to N and approximation coefficients of level N .

Thresholding can be either soft or hard. Hard thresholding zeroes out all the signal values smaller than T_{hr} . Soft thresholding does the same thing, and apart from that, subtracts T_{hr} from the values larger than T_{hr} .

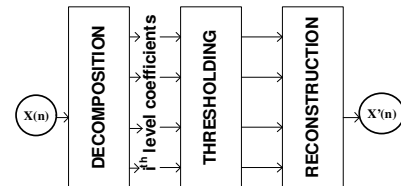


Figure 3. Denoising steps.

III. EMBEDDED IMPLEMENTATION

For the purpose of embedded applications the signal processing algorithms are usually implemented in programmable or reconfigurable devices like MCs or Programmable Logic Devices (PLDs) [7]. Although much faster, the PLD approach is quite expensive, bulky and more difficult for rapid prototyping.

In this research, the above optimized wavelet algorithms are implemented in MSP430 microcontrollers from TI [8]. It is a family of ultra-low power microcontrollers optimized for using in portable battery powered devices like medical ones. As a target chip, the MSP430F169 has been selected, having 16-bit RISC CPU, 16-bit registers, two 16-bits timers, fast 12-bit A/D converter with 8 external input channels, dual 12-bit D/A converter, USART, I2C, DMA, and 48 I/O pins etc.

MSP430F169 on-chip architecture for real-time QRS detection is shown in Fig. 4. The analog ECG signal is fed to the channel of ADC. After digitalization and software processing the real-time output signals are obtained in different forms. Analog form of details $CD_N(n)$ and $CD_{N-1}(n)$, $N=4$, generated by DAC through the pins P6.6 and P6.7. Pulse form, where each pulse indicates detected QRS complex, pin P1.0. ASCII form through the USART's TX pin, where the each record represents the actual RR interval in ms.

Fig. 5 presents MC architecture for wavelet-based denoising. The input signal is digitalized, decomposed by FST, thresholded, and reconstructed by RST. At the end, it is returned in analog form by DAC.

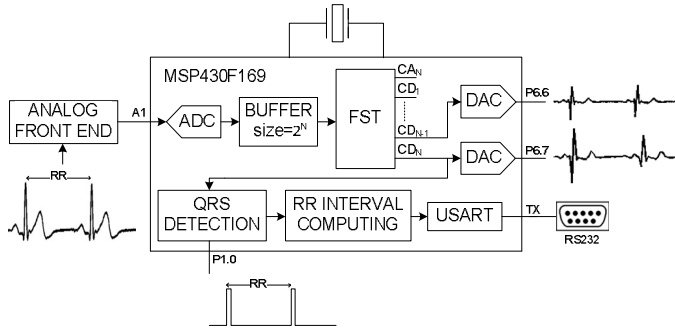


Figure 4. MC architecture for QRS detection.

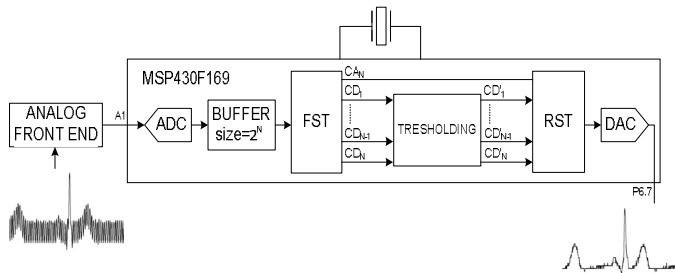


Figure 5. MC architecture for denoising.

The real-time implementation of forward and reverse wavelet transform in software is done through the FST and RST, because of their simplicity and fast calculation. Before processing the signal is digitalized by 12bits A/D converter. The sampling frequency is set at 800Hz for QRS detection and at 762Hz for denoising. The A/D conversion is performed in

an interrupt routine. Between the interrupts the MSP430 MCU switches in sleep mode.

In the case of QRS detection, after A/D conversion, each sample is stored in a circular buffer of 2^N length, where N presents the number of decomposition levels. When the buffer is filled the FST is calculated, while the buffer continues to accept new samples. Then, the detail coefficients $CD_i(n)$ are examined on ZC which is suited between modulus maxima with opposite signs. As it is mentioned the most suitable levels for QRS detection are 3^{th} and 4^{th} , corresponding to $CD_3(n)$ and $CD_4(n)$. In this research the $CD_4(n)$ is preferred. Negative and positive modulus maxima are found by adaptive thresholding technique. 5 successive vectors of 50 CD_4 coefficients are examined. For each of them the maximum $M_{jmax} = \max(CD_4(1..50))$ and minimum $M_{jmin} = \min(CD_4(1..50))$ values are calculated, $j=1..5$. Then the negative (T_1) and positive (T_2) thresholds are defined as:

$$T_1 = \frac{1}{4} \left(\frac{1}{5} \sum_{j=1}^5 M_{jmin} \right), \quad T_2 = \frac{1}{4} \left(\frac{1}{5} \sum_{j=1}^5 M_{jmax} \right). \quad (5)$$

The process repeats with new 5 vectors.

ZC is detected by finding the coefficients associated to the condition $CD_4(n-1) < 0$ and $CD_4(n) > 0$.

Denosing technique follows the steps given in Fig. 3. The thresholding is implemented to detail coefficients of each decomposition level. Also, for every level of decomposition there is a separate threshold. For i^{th} ($i=1..4$) level, 10 successive vectors v of W_i ($i=1..4$) coefficients, $v_{ij}[1..W_i]$ ($i=1..4, j=1..10$) are taken in consideration. For each of them maximal value $A_{i,jmax} = \max(v_{ij}[1..W_i])$ is found. Then the adaptive threshold is defined as:

$$T_i = \frac{1}{10} \left(\sum_{j=1}^{10} A_{i,jmax} \right). \quad (6)$$

IV. RESULTS

On-chip verification is implemented by specially designed tool-set based on ELVIS II⁺ NI Platform [9], microcontroller MSP430 board (Olimex MSP430-P169) and personal computer (PC). MC code is developed in IAR Embedded Workbench Compiler and uploaded to chip. The ECG signals are taken from MIT-BIH database and emulated in analog form by ELVIS platform via LabView virtual instrument. The PPG signals are prerecorded from student volunteers and then reproduced by LabView virtual instrument.

MSP430 chip accepts the emulated signals, performs FST and RST, QRS detection or denoising in real-time. It returns the different signals: analog form of detail coefficients $CD_4(n)$ and $CD_3(n)$, the digital signal with pulses in places of QRS complexes and serial RS232 data in form of ASCII strings with RR intervals in ms. The analog and digital output signals are observed by oscilloscope, while ASCII strings are received by serial terminal emulator.

The original ECG signal and corresponding detail coefficients $CD_4(n)$ taken from P6.7 are shown in Fig. 6, while Fig. 7 presents an ECG signal and impulses from pin P1.0

which correspond to the QRS complexes. In order to determine the QRS detection accuracy the 11,094 heart beats within 5 characteristic files are observed (MIT-BIH Records 101, 103, 202, 230, 234). The average detection rate was about 99.1%. Real-time denoising is tested using prerecorded ECG and PPG signals corrupted by 50Hz or white noise. Fig. 9 (up) illustrates filtering of PPG signal in order to eliminate 50Hz noise, while Fig. 9 (down) shows ECG signal corrupted by white noise and its denoising. The calculation time for FST and RST vary from 2.3 ms and 2.2 ms for 4th to 23.8 ms and 34.0 ms for 8th decomposition level under processor clock of 0.75 MHz, Fig. 8.

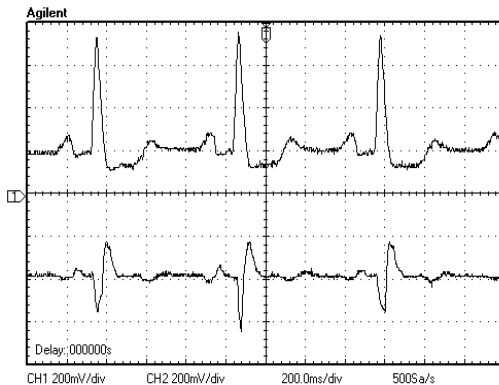


Figure 6. Analog forms of ECG signal and $CD_4(n)$ coefficients calculated by MSP430F169 MC on-line.

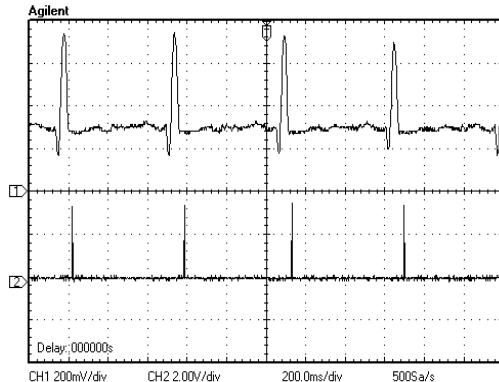


Figure 7. QRS complexes in real signal and corresponding impulses obtained as a result of on-line wavelet based QRS detector.

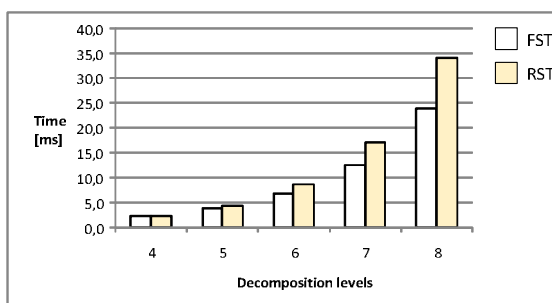


Figure 8. MSP430F169 calculation times for FST and RST.

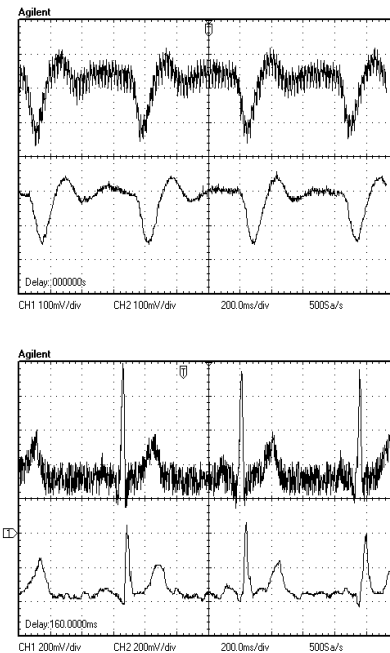


Figure 9. Wavelet based denoising of PPG signal (50Hz noise), up and of ECG signal (white noise), down.

V. CONCLUSION

Wavelet transform is a reliable method for processing of physiological signals. After certain optimizations in term of integer arithmetic it can be easily implemented on general purpose MCs like MSP430 from TI series. The examples of QRS detection and denoising of ECG and PPG signals are elaborated. The systems work in real-time, beyond satisfied detection accuracy and denoising performances. The same approach can be applied with other signals where the embedded implementation of WT can be of benefit.

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